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Simulation of Sensor Fault Diagnosis for Wind Turbine Generators DFIG and PMSM Using Kalman Filter

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Abstract

The fault detection and isolation of generators used in wind turbines gathering interest as to maximize the reliability and avail of distributed energy systems with recent unmatched growth in construction of offshore wind farms. In particular it is interested in performing fault detection and isolation (FDI) of incipient faults affecting the measurements of the three-phase signals (currents) in a controlled DFIG and PMSG. Although different authors have dealt with FDI for sensors in induction machines and in DFIGs, most of them rely on the machine model with constant parameters. However, the parameter uncertainties due to changes in the operating conditions will produce degradation in the performance of such FDI systems. The robust techniques to detect faults are exist but there is a need of extra sensor. This paper proposed a systematic methodology for the design of sensor FDI systems with the following characteristics: i) capable of detecting and isolating incipient additive (bias) faults, ii) robust against changes in the references/disturbances affecting the controlled DFIG and PMSG as well as modeling/parametric uncertainties, iii) residual generation system based on a multi-observer strategy to enhance the isolation process, The designed sensor FDI systems have been validated using measured voltages, as well as simulated data from a controlled DFIG. First the state space models of DFIG and PMSM explained followed by kalman filter introduction and current sensor fault detection using a bank of kalman filter named dedicated Observer Scheme and generalized Observer scheme to detect simultaneous and multiple faults was theorized and simulated using MATLAB simulation tool .The simulation results were summarized with and without Sensor fault.

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Keywords: Wind turbine; kalman filter;Generalized Observer Scheme,;Dedicated Observer Scheme; Fault detection and isolation; current sensor fault.

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1. Introduction

In modern times wind-turbines proffer to a greater part of the world's power production, thereupon the reliability of these turbines is foremost salient. Their down time must be low. The prominent slot of achieving this is to providing thorough advanced fault detection, isolation systems in the wind turbines. Normally Condition monitoring is used to monitor the mechanical parts like gear box etc., an observer centered scheme to identify faults in current sensor was furnished. To test different detection, isolation and accommodation schemes on the wind turbine application [**1**] the functions of the automated control techniques are of following:

Nomenclature

V_{ds}, V_{qs}	Three phase voltage in d-q reference frame
I_{ds}, I_{qs}	Three phase stator currents in d-q reference frame
V_{dr}, V_{qr}	Three phase voltage in d-q reference frame
i_{dr}, i_{qr}	Three phase stator currents in d-q reference frame
R_s, R_r	Stator and rotor resistance of machine per phase
L_s, L_r, L_h	position of Stator, rotor and mutual inductances of machine
ω_r, ω_s	Supply and rotor angular frequencies

- **Monitoring**: Quantitative variants are probed with feature to tolerances, and alarms are mitigated for the operator.
- **Automatic protection**: Whenever in situations of alarming process state, the monitoring function automatically invokes an appropriate countermove;
- **Control with fault diagnosis**: According to the measured values of variables, characteristics are computed, indications are generated through change detection, a fault diagnosis is performed and decisions for balance are built.

Indeed, the summate misstep of a component can escalate the number of accidental break downs of a system. A system, which admitted with the scope of detecting, isolating, identifying, or distinguish faults, is called a fault diagnosis system or fault detection and isolation FDI. The good functioning of the FDI unit is very important to decision making phase. There are many methods to analyze the consistency of the measurements acquired from the monitored system. In ideal conditions the residuals running nearly zero under un-faulty condition and it is very less reactive to noises and disturbances where maxes to faults. The following important step is evaluation of it which attained by proper design of decision rule base termed according to residuals In this paper, we explore dynamic process to validate the measurement using a soft computing algorithm as well shown in Fig.1.

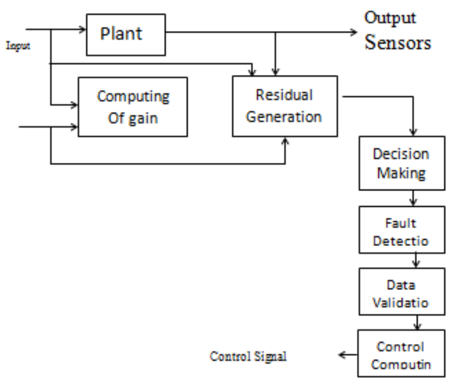


Fig.1 Fault evaluation method

It is beneficial to equip a fault detection service; fault concession can also be done using hardware methodology which currently exists **[2]**, where we have to use an extra sensor, which seems adding extra cost. But here the simulated method requires only a bit of added computations. The cost of computational power will decline in the future based on preceding orientations. Then, the detection and the isolation of multiple and simultaneous sensor faults will be treated using a Kalman filter bank in a Generalized Observer Scheme where we can detect the multiple but non simultaneous faults and a Dedicated Observer Scheme which we can detect the simultaneous faults respectively [5]. The dedicated observer scheme is better choice of implementation of kalman filter bank.

2. Operating Principles of DFIG and PMSM

2.1. DFIG

The schematic diagram **[3]** of the wind turbine and DFIG are fig.2. This is the utmost implementing methodology of DFIG in real time. The Convertor over DFIG consists of two sections: first Crotor –the rotor side converter and followed by Cgrid -the grid side converter. There presents a DC capacitor which in midst connecting these two convertors, admits energy to shell inside and indeed as a DC voltage source. The wind energy apprehend through turbine is mitigated into electrical power by the DFIG and it is valued to grid by rotor and the stator windings.

Where this system can be controlled in three ways:

- Pitch angle control system: Manages the power of generator ensuring assigned power-speed characteristic, termed tracking practice.
- Crotor control system: Manages the reactive current abounding in the converter in turn to control the voltage or the reactive power at grid terminals.
- Cgrid control system: Manages the voltage of the DC link capacitor.

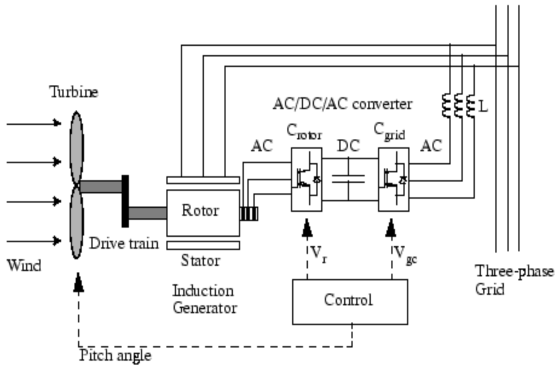


Fig.2 Model of DFIG connected one
(Image Courtesy Matlab)

2.2. PMSM

The stator order of the PMSM is quite matching to a doubly fed induction machine stator or switched reluctance machine stator, where the rotor part varies each [4]. The mere advantage of the PMSM is the rotor side flux formation by the permanent magnets without using the electrical energy. And also the mechanical power used by it is also Low in comparison.

3. Modelling of DFIG and PMSM

3.1. DFIG

While this paper we treated the generator operates in constant speed. The C rotor voltages applied to the rotor are only considered as controlling signals [3]. The amount of power generated can be termed by the measured currents over stator and rotor windings; these measurements are aimed over the project done. The grid side voltages here the stator voltages cannot be considered as controlling parameters or controlling signals but can act as known external inputs.

In Current project, the forward mathematical model of doubly fed induction generator was transformed in d-q reference frame in which the d-axis is selected to accord with stator phase r-axis at t = 0 and the q-axis advances the d axis by 90˚ in the order of rotation. A state-space depiction of the DFIG could be documented as follow

$$\dot{x}(t) = Ax(t) + Bu(t) + Ds(t) \tag{1}$$
$$y(t) = C\dot{x}(t) + Ef(t) \tag{2}$$

$x(t)$ Is state vector – [ids iqs idr iqr]^T
$u(t)$Is control input – [vdr vqr]^T
$s(t)$ Is external known input – [Vds Vqs]^T
$y(t)$ Is output vector and – [y1 y2 y3 y4]^T
$f(t)$ Is fault vector – [f1 f2 f3 f4]^T

Table 1. Parameters of DFIG considered

Rs	Rr	Ls	Lr	Lh	Wr	m
0.00 71	0.00 50	0.17 10	0.15 90	2.90 00	1.75 00	308.31 63

3.2. PMSM

State space Model of PMSM [7]

$$(t) = f\big(x(t)\big) + B(t)v\alpha\beta(t) \tag{3}$$
$$i\alpha\beta = Cx(t) \tag{4}$$
$$f\big(x(t)\big) = \begin{pmatrix} -L^{-1}(Ri\alpha\beta + e) \\ 0 \\ w \end{pmatrix} \tag{5}$$

$$B(t) = \begin{pmatrix} L^{-1} \\ 0^{2X2} \end{pmatrix}, C = [\, I2\ 0^{2x2}\,] \tag{6}$$

$$\dot{x} = A(t)x(t) + B(t)V\alpha\beta(t) \tag{7}$$

$$i\alpha\beta(t) = Cx(t) \tag{8}$$

Table 2.Considered PMSM Parameters

Ld	Lq	Ra	ϴ	Vs	Iα	Iβ	*W*	Ls
0.003	0.006	0.14	1.04	0.92	3.2	2.3	0.79	0.1

4. Kalman filter and dedicated observer scheme

The robust dynamical model been used by the kalman filter to evaluate the state of the particular system. As a mathematical procedure in inevitable filtering uses kalman filter to excerpt a signal from noisy measurements

If presume that the state of the following discrete system is to be estimated:

$$x_{k+1} = Ax_k + Bu_k + w_k \tag{9}$$

$$z_k = Hx_k + v_k \tag{10}$$

A,B,H are matrices of suitable dimension. Where w is the process noise and v is the measurement noise. These above w and v measure form with a 3rd one P, estimate error covariance, the notable three set P,Q,R can be expressed as the masterly adjusting appliance of the filter

The implementation of Kalman filter could be divided in two steps

1) Prediction Step:

$$\hat{x}_k^- = A\hat{x}_{k-1} + Bu_k \tag{11}$$

$$P_k^- = AP_{k-1}A^T + Q \tag{12}$$

2) Correction step:

$$K_k = P_k^- H^T (HP_k^- H^T + R)^{-1} \tag{13}$$

$$\hat{x}_k = \hat{x}_k^- + K_k(z_k - H\hat{x}_k^-) \tag{14}$$

$$P_k = (I - K_k H)P_k^- \tag{15}$$

P – Process covariance noise
R – Measurement covariance noise
P- Estimate error covariance
r_K – Residual where K means Kalman
X_k- to be our *priori* state estimate at step *K*.

The residual r_k (where subscripted letter K means Kalman) is determined by:

$$r_k = z - \hat{x} \tag{16}$$

5. Filter bank for the FDI problem

Filter bank can be used to assess the dynamical response of the system in turn to detect and isolate the fault. There are two types of filter banks each with appropriate schema namely Dedicated Observer scheme and generalized observer scheme A group of observers combined to form a filter bank where they will be given with all inputs and various subsets of outputs of the system and here it presents a declaration unit to assess exactly the fault being happened or not in the particular sensor and which current sensor is under faulty condition by comparing the estimated outputs with the measured values.

5.1. Generalized observer scheme (GOS):

Generalized observer scheme structure for a multi input multi output system depicted the figure 2. The supervised system is accustomed in a way to have four outputs; the generalized observer scheme is preferred to have four observers. Particular nth observer (n = 1 . . . 4) is directed by the input one u and entire outputs exempting y_n. Therefore, the nth observer is arranged to be unvarying to the fault of the measurement of y_n. In this approach residual vector $r_{G,n}$ confides on all excluding nth fault :

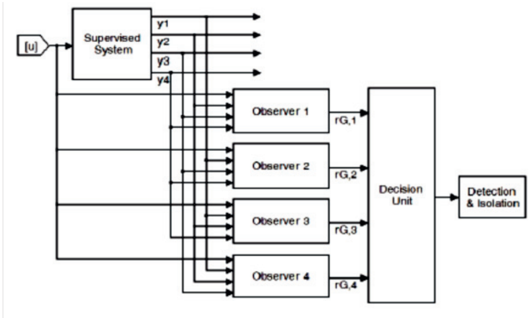


Fig.3 Generalized observer scheme

5.2. Dedicated Observer Scheme:

In this schema particular observer directed with a distinct output shown in fig no. As here it follows the logic like nth observer is only reactive to the occurrence of fault in y_n. Therefore the fault detection and isolation from residual $r_{D,I}$ will be right on; residual value $r_{D,n}$ shows the failure phrase in nth sensor:

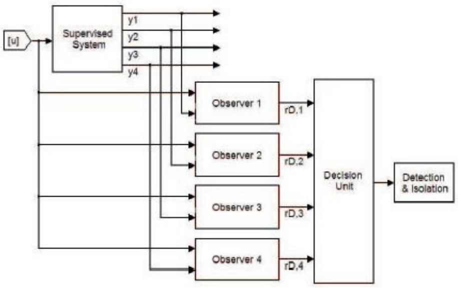


Fig.4 Dedicated observer scheme

The main advantage in dedicated observer scheme is that it can detect and abstract simultaneous faults. Although, the dedicated observer scheme demands a quite strict necessary conditions; supervised system here it must be observable with any given single output. Over the project, the state space representation of the DFIG will meet this condition.

6. FDI for the current sensor faults

Fault detection and isolation for the current sensor faults will be tackled in this section. And the isolation of the fault will be confronted. In implementing the case 2 fault scenarios can be used; termed 1st one comprises multiple but not simultaneous and the 2nd one is simultaneous.

Estimation, Fault Diagnosis Architecture

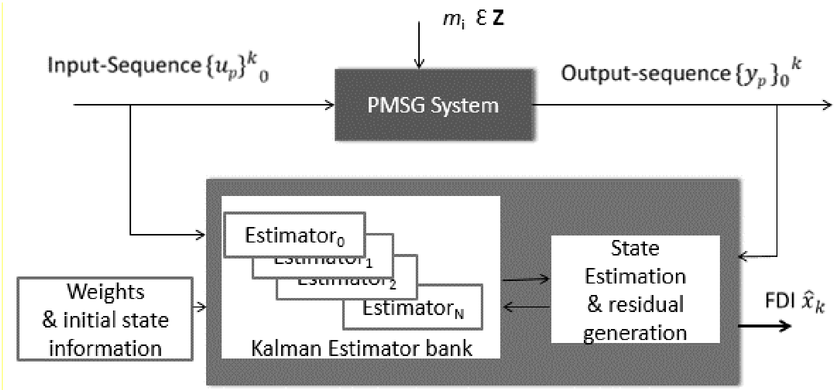


Fig.5 Estimation, Fault Diagnosis Architecture

Table 3. Fault Scenario Number

Event No.	Fault No.	Staring Time(s)
1	F1	50
2	F2	150
3	F3	250
4	F4	350

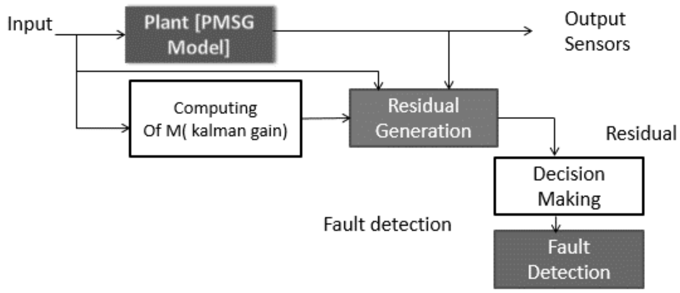


Fig.6 Fault Evaluation method

More Optimization methods:

In order to take advantage of the sequential character of the filter, we should pay attention to its computational cost. Obviously, as the Augmented State Kalman Filter (ASKF) incorporates new measures at every iteration, its size will increase. Given that it essentially involves matrix multiplications.Therefore, ASKF is a good framework to keep track of the state of the dynamic system and; containing all this information in a single state vector. However, it has the drawback of the increasing size of the matrices involved in the filter

This approach has several advantages:

- It is able to integrate all the available information:
- Machines dynamic model, crossover correlation and other sensor measurements (e.g. Voltage -based).
- It continuously updates, with a simple procedure, the state of the machine At the same time, it updates their associated covariance's
- It permits dealing the state estimation error covariance Paug(k) would evolve accordingly to the complexity.

Hence in view of above advantages our work started extension towards implementation of augmented state kalman filter for Doubly fed induction machine

Discretized equation set:

$$X_k + 1 = Ax_k + Bu_k + Fb_k + w^x{}_k \quad (17)$$

$$y_k = Cx_k + Gu_k + Fb_k + V_k \quad (18)$$

$x_k \in R^n$ *is the state vector*; $y_k \in R^m$ *is the observation vector*;
$u_k \in R^r$ *is the input vector*; $b_k \in R^p$ *is the bias vector*;

$$\overline{A} = \begin{bmatrix} A & F \\ 0 & Ip \end{bmatrix} \quad (19)$$

$$\overline{B} = \begin{bmatrix} B \\ 0 \end{bmatrix} \quad (20)$$

$$\overline{C} = [C \ \ G] \quad (21)$$

$$X_k + 1 = \overline{A}x_k + \overline{B}u_k + \overline{w}_k \quad (22)$$

$$y_k = \overline{C}x_k + V_k \quad (23)$$

$$A = \begin{bmatrix} -\frac{R_s}{L_s} & 0 & \frac{\lambda}{L_s} sinv & \frac{w\lambda}{L_s} cosv \\ 0 & -\frac{R_s}{L_s} & \frac{\lambda}{L_s} cosv & \frac{w\lambda}{L_s} cosv \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \qquad B = \begin{bmatrix} \frac{1}{L_s} & 0 \\ 0 & \frac{1}{L_s} \\ 0 & 0 \\ 0 & 0 \end{bmatrix} \quad (24)$$

Augmented State Vector

$$\bar{A} = \begin{bmatrix} -\frac{R_s}{L_s} & 0 & \frac{\lambda}{L_s} sinv & \frac{w\lambda}{L_s} cosv & f(:,1) \\ 0 & -\frac{R_s}{L_s} & \frac{\lambda}{L_s} cosv & \frac{w\lambda}{L_s} cosv & f(:,2) \\ 0 & 0 & 0 & 0 & f(:,3) \\ 0 & 0 & 1 & 0 & f(:,4) \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \quad \bar{B} = \begin{bmatrix} B \\ 0 \end{bmatrix}; \bar{C} = [C \ \ G] \quad (25)$$

Augmented PMSM model

$$X_{k+1} = \bar{A}X_k + \bar{B}u_k + \bar{w}_k$$
$$y_k = Cx_k + Gb_k + v_k \quad (26)$$

The projected work is about current sensor FDI hence all the residual is current which being noted in Ampere. And it is being brought to note that, the unit of residual will not be re-written over anywhere in figures depicted in paper.

7. Results

Simulation results of Residual generation for sensor faults:
DFIG

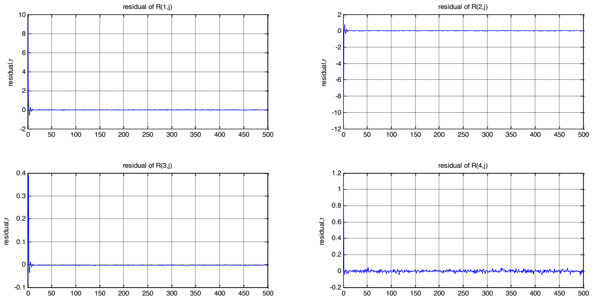


Fig.7 Current sensor residual without fault

The above fig .7 depicts the residual of the current sensor without fault and it represents the residual rD,i(1..4) when sensors are failure-free. One can observe that rD,i(1..4) takes near-zero values.

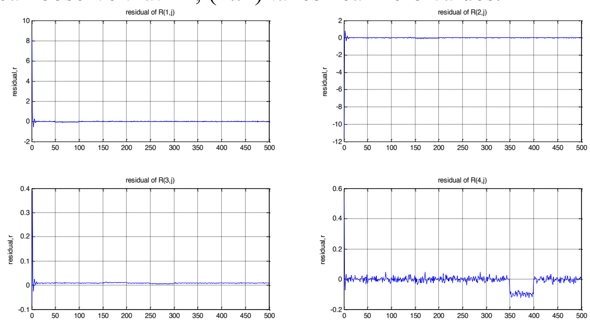
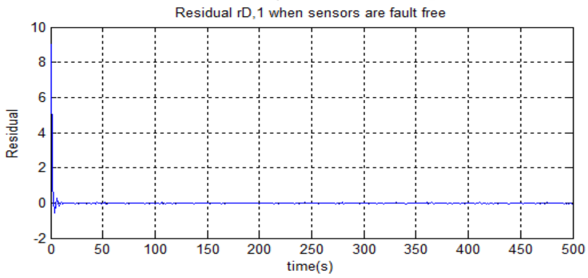


Fig.8 Current sensor residual with fault

When the failure scenario number in table 2 was projected on sensors and the FDI results obtained are depicted in fig no. Certainly, individual residual holds an indicative value whenever the fault of the particular sensor occurs.

The engaged dedicated observer scheme based FDI formulation has presented its extent to detect and to isolate simultaneous faults, even though it is essential that the supervised system is observable for any individual output. Cases which failing this condition can undertake the GOS based FDI formulation to detect and to isolate multiple non-simultaneous faults.

Simulation results of Individual Current Sensor residual generation comparison with and without Fault scenario:



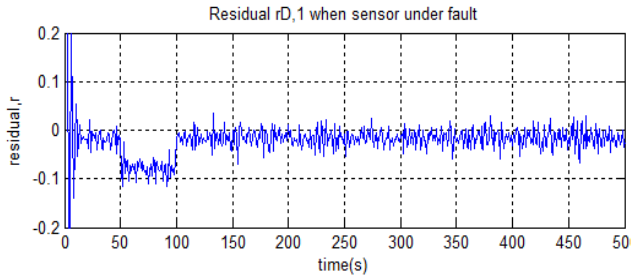


Fig.9 Residual of Current Sensor **Ids** With and without fault

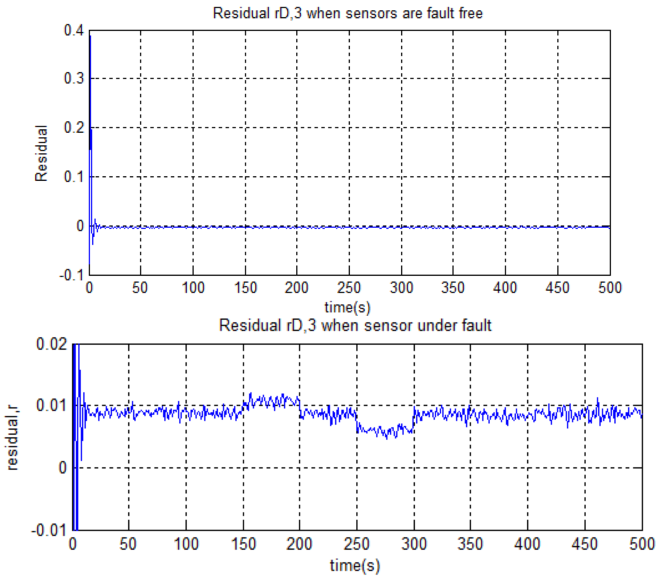


Fig.10.Residual of Current Sensor **Idr** With and without fault

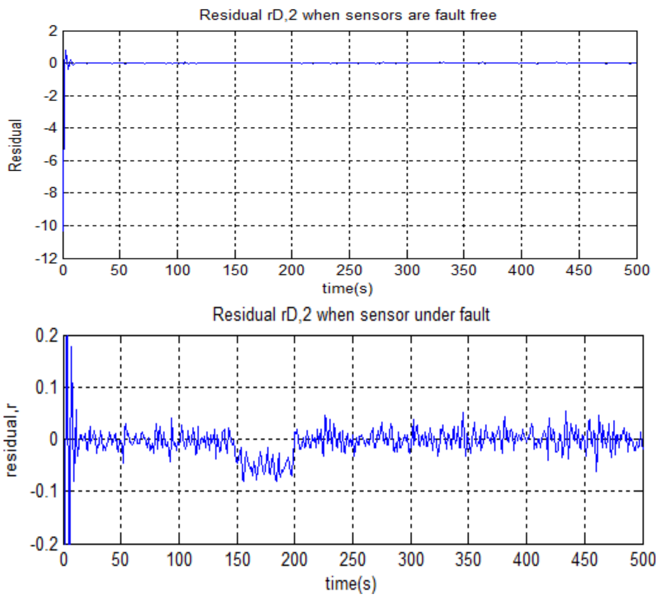


Fig.11 Residual of Current Sensor **Iqs** With and without fault

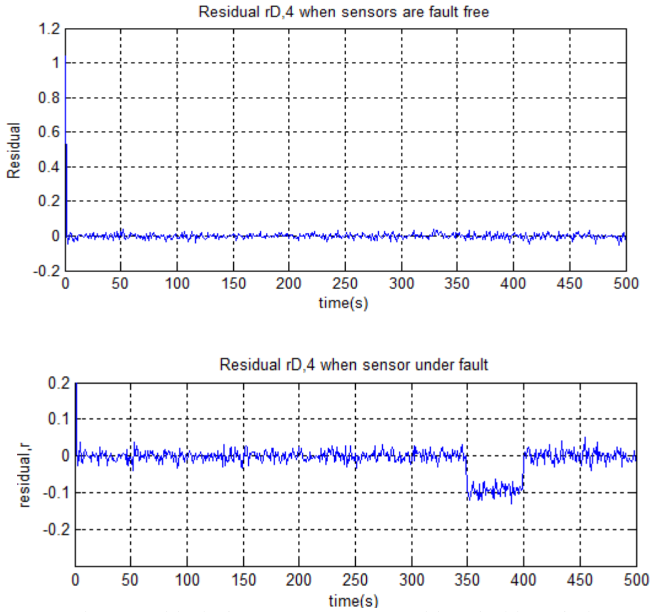


Fig.12 Residual of Current Sensor **Iqr** With and without fault

PMSM Current Sensor fault detection using kalman filter

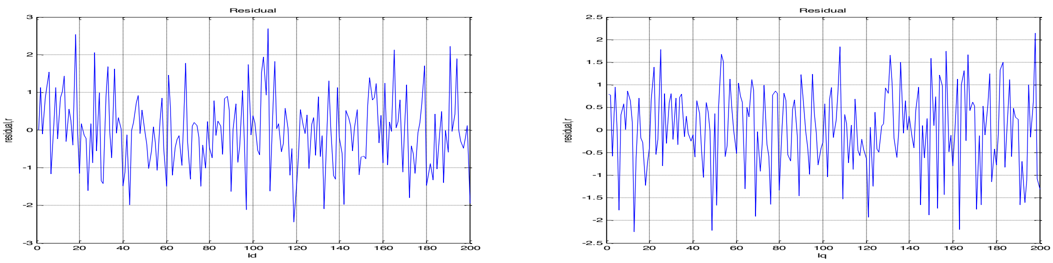


Fig.13 Residual without Current sensor fault

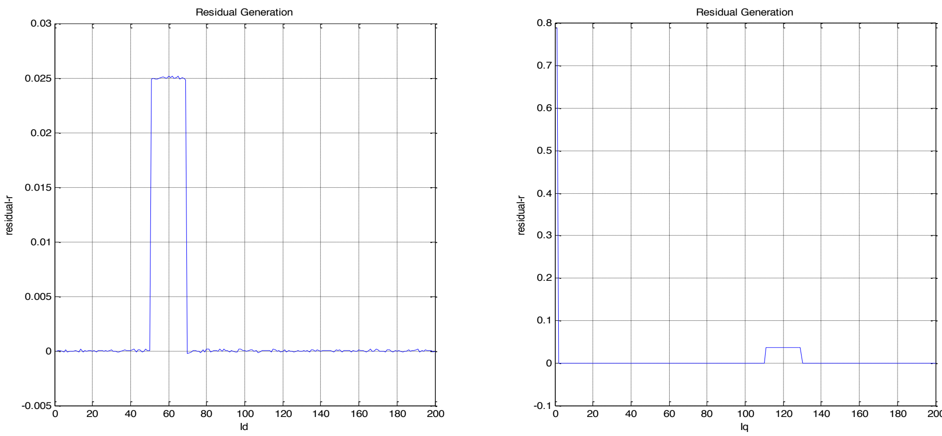


Fig.14 Residual With current sensor fault

Results Augmented state kalman filer

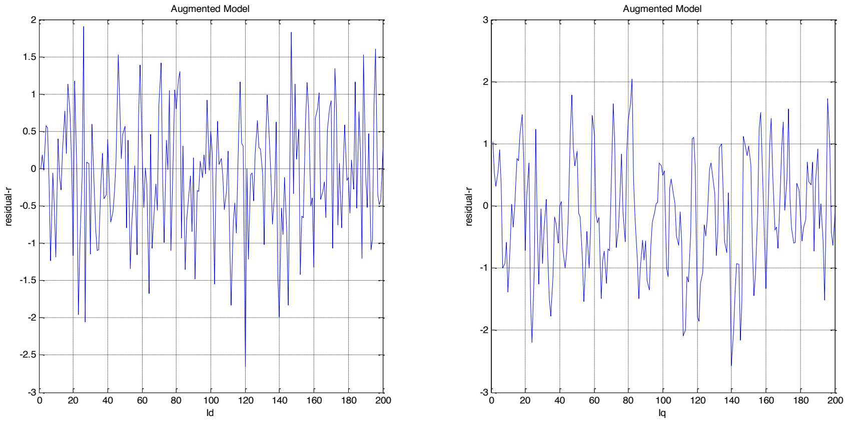


Fig.15 Residual of Augmented state PMSG Without fault

8. Conclusion

In this paper, we've treated the problem of current sensor Fault Detection and Isolation of a doubly feed induction generator and permanent magnet synchronous motor in wind turbine. First of all, the use of a Kalman filter to detect sensor fault has been illustrated. Then, the detection and the isolation of multiple sensor faults were addressed using the Kalman filter bank in a Generalized Observer Scheme. The simultaneous sensor fault was tackled by the Dedicated Observer Scheme. All the multiple faults and simultaneous is detected and located with the appropriated observer scheme. There is no miss detection. And our future work includes fault detection of dynamic systems using augmented stage kalman filter. And also in future dSPACE DS114/DS1103/DS11006 processor board can be used to validate these simulation results, where they translated in C -code using matlab Real-Time Workshop then downloaded to the test bench and the result of the FDI process is display on LEDs.

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